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The Impact of Short-Term Goals on Long-Term Objectives: Evidence from Running Data

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The Impact of Short-Term Goals on Long-Term Objectives.

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The Impact of Short-Term Goals on Long-Term Objectives.

Evidence from Running Data

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Abstract

Theory predicts that goal-setting attenuates impulsiveness and thereby helps people to reach higher long-term threshold levels of consumption, wealth or health. This may imply that people who set goals in short-distance running events are more likely to participate in longer distance runs in the future. We investigate this by analyzing finishing times in over 7,000 major running events of different distances organized in the Netherlands between 1996-2016. We assume that bunching at round finishing times is indicative of goal-setting by a runner. In line with Allen *et al.* (2017), we find strong evidence for bunching at all distances and we find that for the longer distances men bunch more than women. However, runners who bunch are not any more likely to switch to longer distances than others and this is also true for younger runners, who are generally considered more impulsive and thus would benefit more from goal-setting.

JEL classification: D91, Z20

Keywords: goal-setting, bunching, reference points, running.

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I Introduction

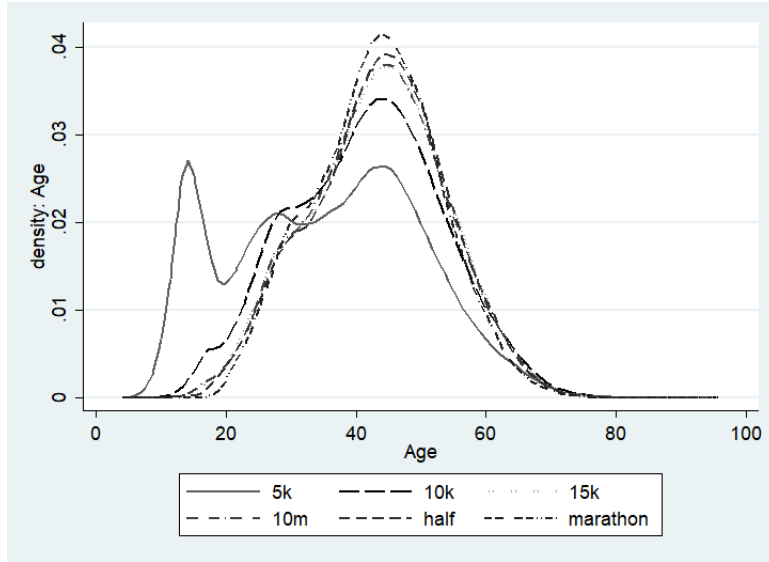
Optimization is a central premise in most of economic theory. The life-cycle model of consumption for example assumes that people smooth their consumption to attain the highest life-time utility. In practice, problems of self-control pose an important impediment to reaching this pinnacle of utility. Goal-setting may help to reign in self-control problems. Indeed, people often set (intermediate) goals to ease their intertemporal planning problems in optimizing their long-run well-being. We set targets on how often we want to visit the gym, how much money we set aside or spend on specific consumption items and how much time or money we spend on others.

Heath *et al.* (1999) is one of the early studies that proposes that goals serve as reference points. Following up on this, recent theoretical research has shown that goal-setting can assist time-inconsistent agents in self-regulation and to reach more ambitious long-run objectives (Koch and Nafziger, 2011; Hsiaw, 2013). Goal-setting may in particular help to attenuate impulsiveness. At the empirical side, Harding and Hsiaw (2014) provide evidence on the effectiveness of goal-setting in reducing residential energy consumption. In general however, field evidence of the effectiveness of goal-setting in intertemporal optimization and the relation between short-term goals and longer-run objectives is scarce. This paper aims to contribute to filling this gap by reporting on the role goal-setting plays in the sports life-time career of runners. To this end, we employ a novel data set containing over three million finishing times of one million unique runners participating in over seven thousand running events of different lengths. Our main objective is to empirically identify whether goal-setting in shorter distance runs predicts future participation in longer-distance runs. Moreover, evidence shows that impulsiveness decreases with age (Eysenck *et al.*, 1985), which suggests that setting time goals may especially help younger people to obtain their long-term running objectives.

We lack direct information on the time goal runners set, therefore we operationalize our hypothesis by assuming that finishing at a round time is indicative of runners having set a time goal. This assumption receives justification from the closely related studies by Allen *et al.* (2017) and Markle *et al.* (forthcoming). Allen *et al.* (2017) convincingly show that marathon runners excessively bunch just before round finishing times such as 3h, 3h30m and 4h. Moreover, by the availability of split times they can establish that runners speed up in the last stretch when this allows them to finish within a

round time limit.¹ In a field study, Markle *et al.* (forthcoming) explicitly asked marathon runners prior to the event to state their time goal, the importance of meeting this goal, and their fastest finishing times in previous 10k and half-marathon runs. They find that marathon runners experience a jump in satisfaction at the point where the finishing time equals the reference point.²

Figure 1: Empirical age distribution different running distances



The main analysis in this paper focuses on the role of bunching in planning. The theoretical work by Hsiaw (2013) predicts a connection between goal-setting and attaining longer-run objectives. In our context, this implies that runners who do not coincidentally participate in a run but aim to attain a longer-run objective like reaching a higher fitness level benefit from setting time goals. Just as the time goals, these longer-run objectives are not directly observed. For this reason, we assume that future participation in longer distance runs is correlated with an agent having longer-run sports objectives. In that case, we expect a positive correlation at the individual level between the propensity to bunch at a round time and future participation in longer distance runs. Of course, the causality may run in both directions: individuals with long-run objectives may be more likely to set time-goals but successfully setting time goals may also induce people to formulate longer horizon objectives. In fact,

¹Allen et al. (2016, p. 14) state, without reporting estimates, that they also find evidence of bunching for the shorter 10 mile and half marathon distances.

²Other studies using running data or sports data more generally to study planning problems using running include Grant (2016) and Pope and Simonsohn (2011). Bunching is also an important and much studied phenomenon in other areas than sports. See Kleven (2016) for an excellent review of this literature.

Hsiaw (2013)’s model also does not offer guidance regarding the direction of causality.

The earlier cited work by Allen *et al.* (2017) and Markle *et al.* (forthcoming) also considers the idea that the observed bunching at round times may result from runners having time goals that act as reference points. However, while we consider the connection between these time goals and long-term objectives like participating in longer distance runs, they take a within-race perspective and by and large ignore the ‘career’ of a runner across races. Allen *et al.* (2017) find evidence that within a race, runners plan and pace towards round reference points and Markle *et al.* (forthcoming) show that marathon runners with explicit single-run time goals strive to meet them. Allen *et al.* (2017) plausibly rule out that the round number bunching in their data is driven by explicit rewards such as qualifying for the Boston marathon, or by institutional details such as the presence of pacesetters. This however leaves the question which underlying behavioral primitive may lead to round time bunching. Is it just a cognitive phenomenon (we are wired such that we naturally compare our running results with round reference points) or do these reference points help to reach more distant objectives?³ This is the question we address by considering the connection between round number bunching and future participation in longer-distance runs.

As a second contribution, this paper complements and extends previous empirical work on running data in two important ways. First, the group of people that run marathons arguably is a highly selected group likely to be strongly motivated by long-run objectives related to health and sporty aspirations.⁴ Moreover, as Figure 1 shows, presumably because of the longer distance, people start running (half) marathons at a later age than the shorter distances. The youngest marathon runners are about twenty years old, for the 10k this is about twelve years. Besides the age-distance relation, many people who have run shorter distances are likely to drop out and never get to running longer distances such as the (half) marathon. For these reasons, the question whether the findings on bunching by marathon runners extend to a more general pool of runners, running shorter distances, is of interest in its own right. Exactly this is what the first part of our analysis aims to accomplish by replicating the findings by Allen *et al.* (2017) for a broader population of runs including marathons as well as shorter distances.

³Pun intended.

⁴The “52 reasons to run a marathon” of the Runner’s World magazine lists “nice quads/calves/buttocks/abs” as reasons 9 to 12 (<https://www.runnersworld.com/chatter/52-reasons-to-run-a-marathon>, visited November 10, 2017).

Our key empirical findings are the following: First, we replicate the findings of Allen *et al.* (2017), not only for the marathon but also for the shorter distances 10k and 21k. We graphically present the distribution of finishing times and estimate the counterfactual distribution, which allows us to identify the excess mass in the distribution prior to the reference time. Using bootstrapping, we report *t*-statistics of the estimated counterfactual number of runners. We find evidence of bunching for almost all distances, observing the highest excess mass of 32.9% in the bunching region of finishing times in the marathon. The reference times corresponding to the top three regions with the highest excess mass in the marathon are the 3h, 4h and 3h30m region. This top three coincides with the findings of Allen *et al.* (2017). For shorter distances we find a moderate amount of excess mass, reaching a maximum of 11%. While the highest number of finishers is in the 10k run, there exists only around 4% of excess mass in the distribution observed at 40 and 50 minutes.

Second, making use of available background information on runners, we investigate the origins of bunching. We analyse the relationship between the probability to bunch for a given distance and runner/event specific variables such as age, gender, running experience, being member of a athletics club and whether or not the run is a contest. In this part of the analysis we will restrict the bunching period from 2m to 75 seconds. This more restrictive definition is chosen to mitigate the possibility that finishing times will be misclassified as bunching times when they fall into the bunching period by pure chance. We find that the probability to bunching reduces with age for distances up to 10k and increases with the cumulative number of kilometers run. Female runners are more likely than men to bunch in shorter distances, but the opposite holds for longer distances. When the cumulative distance run serves as a good proxy for experience, we find an inverted U-shape relation between the propensity to bunch and experience.

Finally we analyse the running career of individuals, questioning whether bunching in shorter distance runs predicts future participation in longer distance runs. Our regression estimates show that runners who finish at a round time goals are not any more likely to switch to longer distances than others. This negative result continues to hold if we zoom in on the younger runners, who allegedly are more impulsive and thus would benefit more from goal-setting. In other words, we do not find evidence that the bunching that we observe in our data is motivated by the presence of longer-run

objectives.

2 Conceptual framework

Hsiaw (2013) shows in a theoretical model that goal-setting can assist time-inconsistent agents to reach more ambitious long-run objectives. To motivate and set the stage for the empirical analysis that follows, we briefly introduce her model.⁵ Hsiaw (2013, p. 604) considers the continuous-time optimal stopping problem of an infinitely lived agent who has the option to invest in a project. At time t , the agent knows current value of the project's payoff $x_t \in [0, \infty)$. Based on this information, she has to decide whether to stop or wait. When she waits, the development of the project's payoff is described as a geometric Brownian motion: $dx_t = \mu x_t dt + \sigma x_t dz$, with z a standard Wiener process, μ the average growth rate of x_t and σ its standard deviation per unit time. When the agent stops at time \bar{t} , the project yields a lump-sum terminal payoff $x_{\bar{t}}$ and she incurs a stopping cost equal to $I > 0$. Hsiaw interprets the value x_t as a wealth level. Given our sports setting, we will instead view x_t as a personal health payoff and correspondingly consider the project to be an investment in one's health. In the empirical part, we operationalize this by assuming that running longer distances generates a higher underlying level of health. In this context, an agent "waits" as long as she continues to participate in official runs and "stops" when she quits participation. We readily concede that for our health interpretation of x_t , the geometric Brownian motion assumption is more problematic than when x_t is considered to represent wealth. In fact, we implicitly assume that by stopping an agent can lock in a health level, whereas her health may improve or deteriorate when she continues to participate in official runs. The model does neither include interim payoffs or costs prior to stopping, that is, running activities do not generate immediate payoffs or cost. This however is without loss of generality, including an observable stochastic flow payoff leads to qualitatively similar results (Hsiaw, 2013, fn. 3).

The agent's time preferences are modeled according to the continuous-time hyperbolic discounting model formulated by Harris and Laibson (2013). At any time s , the agent dissects time into a "present" of (stochastic) length τ_s and a "future" that starts at time $s + \tau_s$ and lasts forever. The essence is that in the present the agent does not know exactly when the future will arrive but she knows that

⁵For further details, we refer to Hsiaw (2013).

at that time $s + \tau_s$, she will be replaced by a new self who will control decision-making from then on till the next future time $s + \tau_s + \tau_{s+\tau_s}$. The possibility for present-biased preferences is introduced with the discount function. Each self s is governed by a stochastic discount function $D_s(t)$:

$$D_s(t) = \begin{cases} e^{-\rho(t-s)} & \text{if } t \in [s, s + \tau_s), \\ \beta e^{-\rho(t-s)} & \text{if } t \in [s + \tau_s, \infty), \end{cases} \quad (1)$$

with $\beta \in [0, 1]$ and $\rho > 0$.⁶ The parameter β is a measure of the impatience or impulsiveness of the agent. When $\beta = 1$, the preferences in equation (1) are akin to those of a time-consistent exponential discounter, for values $\beta < 1$, the agent is biased towards the present.

The agent's utility at the stopping time is the sum of a consumption utility and a comparison-utility that depends on a reference point:

$$u(x_{\bar{t}}|r_{\bar{t}}; I) = x_{\bar{t}} - I + \eta(x_{\bar{t}} - I - r_{\bar{t}}), \quad (2)$$

with $\eta \geq 0$ and reference point $r_{\bar{t}}$. The agent's consumption utility of stopping at time \bar{t} simply equals her terminal payoff net of stopping cost. The agent also incurs the comparison utility at the time of stopping, that is, no comparison utility is received when waiting.⁷ Comparison utility is modeled as a linear function with no kink at the reference point. In other words, the agent does not exhibit loss aversion.⁸ The reference point $r_{\bar{t}}$ is formed by the agent's goal at time \bar{t} .

The parameter η represents the agent's degree of reference-dependence or 'goal commitment'. The reference point is endogenously determined. However, the decision making agent at time s , 'self s ', faces a goal r_s set by her previous self and she cannot change this during her lifetime. In a similar vein, the future self $s + \tau_s$ inherits a goal $r_{s+\tau_s}$ set by self s . It is this "goal stickiness" that enables the agent to carry forward goal commitment: the agent is committed to evaluate her decisions against an inherited reference point. To close the model, it is assumed that each self's inherited goals are con-

⁶The restriction $\rho > \mu$ guarantees that the agent never finds it optimal to wait forever.

⁷Hsiaw justifies this modeling choice with references to the literature on mental accounting that provides evidence that individuals only experience paper gains and losses only when they liquidate their assets (Odean, 1998; Thaler, 1999).

⁸This is contrast to Kőszegi and Rabin (2006, 2007). Hsiaw (2013) shows that the loss aversion assumption is not needed for goals to affect behavior. The absence of loss aversion is also the reason that the second part is referred to as 'comparison utility' instead of 'gain-loss utility'.

strained by rational expectations. Moreover, agents are assumed to be sophisticated in the sense that they are aware of the present-biasedness of their future selves.

At any time s , the agent chooses the stopping rule that determines a (random) stopping time \bar{t} that maximizes the expected present value of his overall utility, i.e.

$$\max_{\bar{t}} E_s[D_s(\bar{t}) (u(x_{\bar{t}}|r_{\bar{t}}; I))],$$

with E_s the conditional expectation at time s .

The central prediction on equilibrium behavior that follows from this model, relevant to our setting is the following:⁹

By inducing more patient behavior, reference dependence attenuates impulsiveness in a stationary equilibrium with endogenous goals: $\partial \bar{x} / \partial \eta > 0$.

In other words, reference-dependence (high η) serves as a countervailing power to impulsiveness (low β). However, another implication relevant for our setting but not made explicit by Hsiaw is that the impact of reference dependence in attaining a threshold payoff is decreasing in the impulsiveness of the individual: $\partial^2 \bar{x} / \partial \eta \partial \beta > 0$.¹⁰ That is, goal-setting is less effective in increasing the threshold \bar{x} the more impulsive the agent is.

2.1 Research questions

What are the implications of this model for bunching if we assume that bunching at round times is the result of reference-dependent preferences, specifically, time-goal setting of runners? The first implication is that bunching should not be observed when agents attach zero weight ($\eta = 0$) to comparison utility. Allen *et al.* (2017) have identified bunching behavior in marathons, suggesting that $\eta > 0$ and runners do set time-goals. The first part of our analysis will add to this evidence, for shorter distances as well.

⁹Proposition 2 in Hsiaw (2013).

¹⁰A formal proof: The equilibrium expression for \bar{x} (cf. Hsiaw, equation 11) is $\bar{x} = \left(\frac{\bar{\gamma}}{\bar{\gamma}-1-\eta} \right) I$ with $\eta < \bar{\gamma} - 1$, $\bar{\gamma} > 1$ and $\bar{\gamma}$ a function of β . Denote $\partial \bar{\gamma} / \partial \beta \equiv \phi$ and $\bar{\gamma} - 1 - \eta \equiv \theta > 0$. Then $\frac{\partial^2 \bar{x}}{\partial \beta \partial \eta} = \phi(1 + \eta + \bar{\gamma})I/\theta^3 > 0$.

As an intermediate step in answering the question regarding the connection between short-term time goals and long-term objectives, we relate the propensity to bunch to a number of runner and race characteristics. How does bunching vary by age, gender, running experience and the distance of the run? Next we delve into the question to which extent bunching in shorter distances predicts future participation in longer distance runs. To this end, we limit our sample to the finishing times of runners who at a given point in time did not participate in a run of length ℓ . We define a dummy-variable which takes on the value 1 if this runner will in the future participate in a run of length ℓ or more and 0 otherwise. To find the incremental effect of bunching on the probability to move to a higher distance, we regress this variable on a bunching dummy and a host of other variables. Hsiaw (2013) finds that individuals who put higher weight on comparison utility will set (and reach) higher goals. Evidence of a correlation between bunching and longer distance participation would be in line with this model. As stated above, one implication of the model is for more impulsive agents, setting goals is less effective in increasing the threshold \bar{x} . This implies that when runners set round time-goals not solely for immediate gratification but to accomplish longer-term objectives, exemplified by running longer distances, our bunching dummy is a better predictor of future running distances in less impulsive subpopulations. Given evidence from psychology that females are more impulsive than males and that impulsiveness is decreasing with age, we expect the correlation between bunching and longer-distance participation to be higher for males and older runners.

3 Data

Our data are retrieved from a public site www.uitslagen.nl that collects the results of almost all major running events organized in the Netherlands from 1996 to 2016. The estimation sample used in this paper contains 3,072,903 finishing times from 7,123 different runs of distance 5k(kilometer), 10k, 15k, 10 miles (16.090k), half marathon/21k or marathon. The official marathon length is 42.195 kilometer (26.2-mile) and the official half marathon length is 21.1k. In our data, we classify all runs with a length of 21k to 21.1k as half marathons, just as we classify all runs with a length of 16k to 16.1k as

10 mile runs.¹¹ With regard to finishing time, a distinction can be made between a runner’s clock time (the time between the start of the race till the runner passes the finishing line) and his/her chip time (the time between the runner passing the starting and finishing line). Following Allen *et al.* (2017), we will throughout use chip-time whenever available; in cases where we have only a single finishing time, we will treat it as if it were a chip time.¹²

3.1 Descriptive statistics

Table 1 shows the number of unique finishing times for each distance. As the table shows, with over 1 million observations, the 10k distance is the distance most frequently run, followed by the 5k and half marathon distance. The remaining distances are less commonly observed but still have over 150,000 finishing times. Next to the finishing time, our data also includes relevant background variables on the runner, such as the runner’s gender, year-of birth, and the reported association of the runner.¹³ The latter variable is either the name of the village in which the runner resides or the name of the athletics club of which the runner is a member. We use this as an indicator of whether an individual runs alone or as part of team and investigate whether being part of a club influences goal-setting.¹⁴ Table 2 provides details on these variables for each distance category. We observe that the average age is increasing in distance with the most notable jump between 5k and 10k. We find a similar effect for gender: the majority of runners who completes 5k is female (55%) but this balance decisively tilts towards males for the 10k (only 37% females), and this trend continues in the half marathon and marathon, in which the percentage of female participants is 33% and 17%, respectively.

¹¹The complete data set contains 5,321,614 finishing times, from 10,703 different events. A considerable number of runs are “street runs” without a specified distance (983,678 records) or non-major distances (1,212,988 records). Details on the data collection, the way the data has been organized and details on the composition of the estimation sample can be found in Online Appendix A.

¹²The chip time technology has been adopted quickly. For the races before the year 2000, chip time is not available; from the year 2003 onwards, the majority of finishing times in our data are chip times.

¹³To identify a runner’s gender, we matched the first given name of each observation with a data base of the 10,000 most common given names in the Netherlands. This data base contains all given names that have been given 27 times or more to children born in the Netherlands in the time period 1983-2006 according to the administrative records of the Sociale Verzekeringsbank. In case of a match, the result can be that the runner is classified as a male, female or ambiguous (some names like “Anne” are used for boys and girls). In case of no match, the second and third given names are considered to identify the gender. In total, in 4,797,905 cases the gender of the runner is determined (2,920,426 male observations; 1,499,673 female and 377,806 ambiguous).

¹⁴In contrast to Allen *et al.* (2017), our data does not contain split times; unlike Markle *et al.* (forthcoming) we do not have survey evidence on runners’ time goals.

Table 1: By distance summary of unique finishing times

Distance	No. finishing times
5k	726,408
10k	1,207,118
15k	220,486
10m	191,913
half	569,134
marathon	157,250
Total	3,072,309

We utilize the fact that our data includes personal identifiers such as name, birth year and place of residence. This information enables us to link finishing times of the same individual and thereby to reconstruct individual running careers. As runners need to fill in their personal details every time they sign up for a run (there is no central registry), it happens that the same individual is registered under different names, dependent on whether the full name or only one or more initials are used (“jan jansen”; “j jansen”, “j m jansen”) or simple spelling mistakes (“jan janssen”, “jan janse”). We address this by considering the similarity of the given and family name of different observations using the Jaro-Winkler distance metric (Winkler, 1999). The Jaro-Winkler distance has been developed specifically to detect duplicates in record linkage that result from typos. The Jaro-Winkler distance metric returns a value between 0 and 1. A score of 0 means an exact match and a score of 1 implies no similarity. One feature of the Jaro-Winkler distance metric is that the substitution of two characters that are close is considered less important than the substitution of two characters further apart. We use a threshold value of 0.15 with all pairs of names being considered duplicates if the Jaro-Winkler score on both the given and family name was smaller or equal to 0.15. A summary of the number of runs per unique runner when the (unbalanced) panel is constructed in this manner is given in Table 3. As the table shows, the majority of runners (57%) participates only once. About 5% of all runners are frequent runners with more than ten finishing times in the data base for the distances considered.

Having identified for each unique runner a sequence of finishing times and distances run, we can answer more precisely the question how the wedge between male and female participation grows for longer distances: Is this because – compared to men – less females start to run at later ages or because less females continue to run and make the transition to longer distances? What is the chance that the

Table 2: Summary Statistics Distances

	mean	sd	p10	p90
10k				
Age	41.64	11.70	26	57
Gender	0.626	0.484	0	1
Speed	11.75	2.058	9.377	14.54
Club	0.139	0.346	0	1
10m				
Age	43.18	10.62	29	57
Gender	0.747	0.435	0	1
Speed	11.85	1.862	9.705	14.27
Club	0.170	0.375	0	1
15k				
Age	43.36	10.70	29	57
Gender	0.738	0.440	0	1
Speed	11.88	1.863	9.695	14.35
Club	0.171	0.377	0	1
5k				
Age	35.47	14.46	15	54
Gender	0.455	0.498	0	1
Speed	11.10	2.354	8.483	14.48
Club	0.111	0.314	0	1
half				
Age	43.38	10.42	29	57
Gender	0.672	0.469	0	1
Speed	11.62	1.742	9.591	13.87
Club	0.166	0.372	0	1
marathon				
Age	43.07	9.761	30	56
Gender	0.830	0.376	0	1
Speed	10.98	1.767	8.928	13.27
Club	0.159	0.366	0	1
Total				
Age	40.83	12.34	24	56
Gender	0.623	0.485	0	1
Speed	11.55	2.063	9.155	14.31
Club	0.143	0.350	0	1
N	3072309			

Table 3: Summary: Number of runs per unique runner.

no. runs	no. runners	percent	cum. perc.
1	583,313	57.6	57.6
2	159,171	15.7	73.3
3	77,798	7.7	80.9
4	46,020	4.5	85.5
5	30,099	3.0	88.5
6	21,420	2.1	90.6
7	15,959	1.6	92.1
8	12,005	1.2	93.3
9	9,611	0.9	94.3
10	7,637	0.8	95.0
>10	50,365	5.0	100.0
Total	1,013,398		

Note: The five most active runners completed 268, 285, 309, 396 and 534 runs, respectively.

next run of an individual who currently runs a distance ℓ is a run with length $\ell' > \ell$? Table 4 depicts this transition matrix based on our data. A look at the table by column shows that when a runner participates in a run of length ℓ , most likely the previous run in which the runner participated was also of length ℓ . This holds for males and females alike.¹⁵ However, a row-wise comparison between males and females reveals interesting differences. For every distance, the likelihood to quit after completion is considerably higher for women than for men. The differences, summarized in percentage point differences at the bottom of the table, indicate that a higher percentage of males increases the distance of the next run and that females, conditional of having completed a run of length ℓ , are 6 up to 11 percentage points more likely to quit running. Put another way, when one observes a female participating in a 10k or 21k run, chances are 29 to 33% that this is her final run; for males the corresponding numbers are 20 and 24%.

¹⁵For example, in 32.7% of all cases the previous run of a man who runs 21k has also been a 21k run.

Table 4: Matrix of conditional transition probabilities.

Distance _n	Next distance (Distance _{n+1})						
	5k	10k	15k	10 mile	21k	marathon	none
MALES							
5k	0.392	0.180	0.021	0.017	0.036	0.005	0.349
10k	0.071	0.447	0.060	0.048	0.120	0.019	0.235
15k	0.042	0.246	0.187	0.067	0.228	0.048	0.182
10m	0.040	0.242	0.089	0.177	0.216	0.035	0.201
half	0.032	0.226	0.072	0.066	0.328	0.078	0.198
marathon	0.022	0.134	0.063	0.037	0.192	0.176	0.376
FEMALES							
5k	0.351	0.150	0.012	0.008	0.019	0.002	0.459
10k	0.104	0.402	0.049	0.029	0.082	0.009	0.327
15k	0.061	0.258	0.135	0.049	0.214	0.035	0.248
10m	0.060	0.232	0.067	0.137	0.212	0.022	0.269
half	0.049	0.223	0.062	0.050	0.270	0.053	0.292
marathon	0.039	0.148	0.057	0.032	0.177	0.110	0.437
Difference males vs. females							
5k	0.041	0.030	0.009	0.009	0.017	0.004	-0.110
10k	-0.033	0.045	0.012	0.019	0.039	0.010	-0.091
15k	-0.019	-0.012	0.052	0.017	0.014	0.013	-0.065
10m	-0.020	0.010	0.022	0.040	0.004	0.012	-0.068
half	-0.018	0.004	0.010	0.016	0.057	0.025	-0.094
marathon	-0.017	-0.014	0.006	0.005	0.015	0.066	-0.061

The last finishing time in our data of active runners is by construction 2016. To avoid that these records are interpreted as the final run in the career of these runners, we limited attention in constructing this table to pairs of runs $(n, n + 1)$ for which finishing time n was recorded before 2016.

4 Empirical results

Our empirical analysis consists of three parts. First, we consider the aggregate distribution of finishing times per distance to see whether there are indications of excess mass just before the 10-minute marks. Second, having established excess mass for all distances, we then peer deeper into the origins of bunching behavior. Is there a relation between the propensity to bunch just before 10-minute marks and runner and race characteristics, such as age, gender and distance? Third, the predictive power of bunching is assessed: Are individuals who bunch more likely to shift to running longer distances? If so, their bunching behavior (short-term goal setting) may originate from a longer-run objective they have in mind but is unobserved by the researcher.

4.1 Bunching of finishing times

As a first step towards identifying whether a correlation exists between short-run goals and long-run objectives, we investigate whether there exists an excess mass just before round numbers are observed for different distances. We closely follow Allen *et al* (2017) in using the non-parametric excess mass test developed by Chetty (2011).

The Chetty(2011) methodology suggests the following steps: First, we define the round finishing times (reference points) around which we expect bunching, then we estimate a counterfactual distribution while excluding the observations in the bunching region. The difference between the actual and counterfactual distribution in the bunching region is the measure of excess mass. The counterfactual distribution is obtained by fitting a quintic polynomial to the distribution around the round number by excluding the bunching period. There are several parameters of consideration in the following procedure: the reference time, the bunching region, the analysed interval of distribution for the quintic regression and the size of the bin in the distribution. To keep our analysis comparable to Allen *et al.* (2017) we choose a 4m bunching region and a 16m analysed interval (8m before and 8m after the round time) for the marathon and half of these values for the half-marathon. The choice of bin size depends on data availability. We benefit from having a large number of observations per finishing time. This allows us to reduce the bin size while keeping a substantial number of finishing times per each bin. The bin size in our analysis is 15 seconds as in Allen *et al.* (2017). For consistency, we use for

the shorter 10 mile, 15k, 10k and 5k runs the same parameters as for the half-marathon. Figure 2 shows the distribution of finishing times for the 21k and marathon around some selected 10 minute points and Figure 3 does the same for 5 and 10k runs.¹⁶

For the marathon, we observe a clear excess mass just before the 3h00m, 3h30m, 4h00m and (to a lesser extent) 4h30m. For the half marathon, a similar kink in the distribution shows before the 1h30m and 2h00m finishing time. For the half marathon, bunching is less pronounced than for the marathon, despite the number of observations being higher.

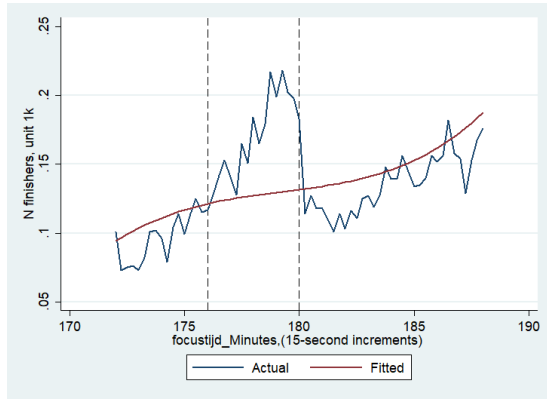
Turning attention to the bunching region, Table 5 presents the actual and estimated number of finishers before the reference time. We also report t -statistics of the estimated values obtained by bootstrapping with 1,000 iterations. In all reported distances and reference times (except for the 5k 30 minute reference) we observe significant excess mass of finishers. The highest value of excess mass of 32.9% is observed for the 3 hour finishing time in the marathon. Allen *et al.* (2017) report the highest excess mass for the same time with a value of 24.2%. The second and third highest excess mass values (4h and 3h30m points) also coincide with the analysis in Allen *et al.* (2017). Table 5 confirms the graphical evidence that even though the number of finishers is the highest for the 10k run, relatively more bunching is observed in the marathon.

In sum, the evidence in this section adds to the earlier evidence provided by Allen *et al.* (2017) that runners do set time goals and thus do attach weight ($\eta > 0$) to comparison utility that depends on a reference point.

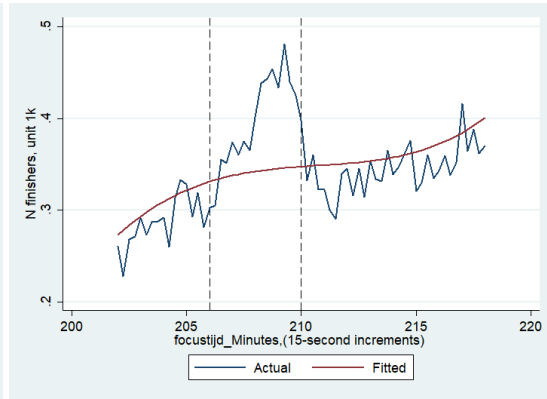
4.2 Bunching and personal traits

Whereas the previous section showed that bunching just before 10-minute intervals is observed in runs of all distances, the next question of interest is whether we can say more about the origins of bunching: which people bunch and does this depend on their past performance or objectives for the future? Here we make use of the circumstance that our data envelopes large part of the universe of runs held in the Netherlands, which enables us to track runners over time. We not only observe important personal characteristics of a runner such as age and gender but also the runner's history, the cumulative

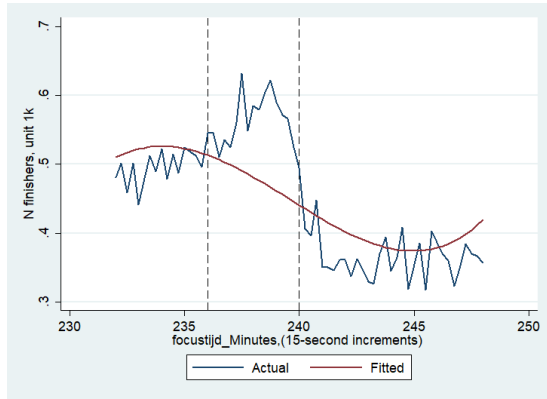
¹⁶Figures A1-A3 in the Online Appendix show the results for all 10 minutes between the 10th and 90th percentile finishing time.



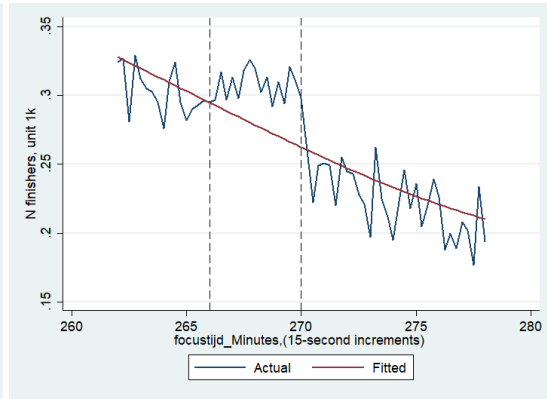
(a) Marathon 3hoom.



(b) Marathon 3h30m.



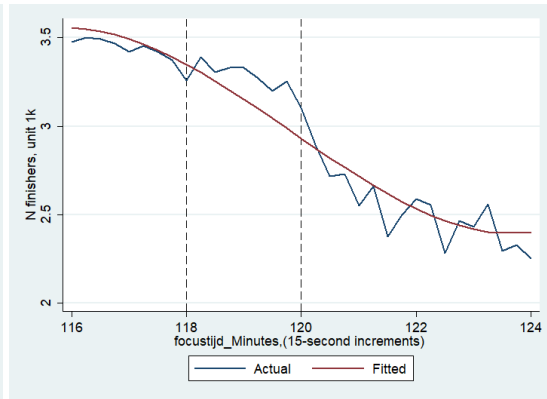
(c) Marathon 4hoom.



(d) Marathon 4h30m.

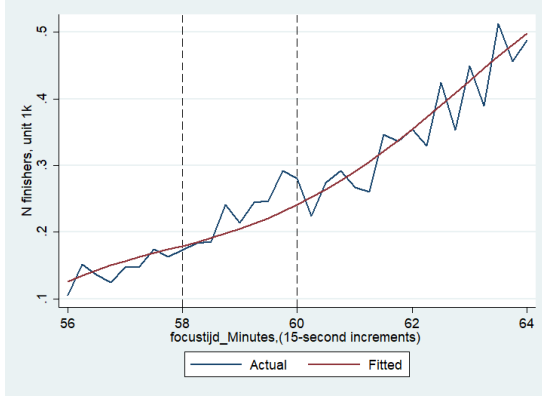


(e) Half marathon 1h30m.

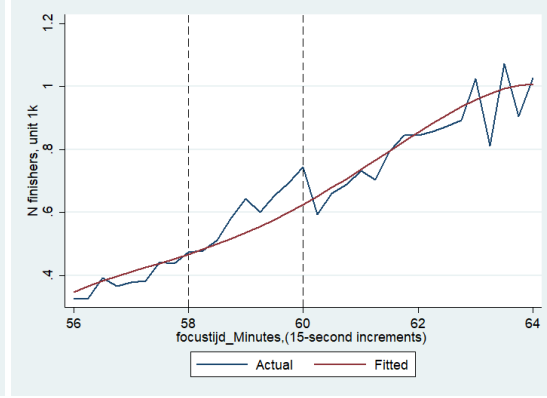


(f) Half marathon 2hoom.

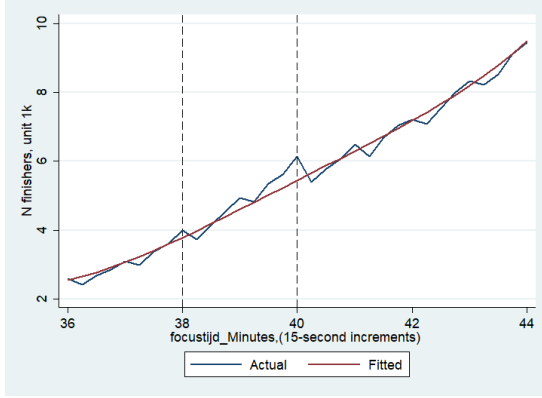
Figure 2: Distribution of the number of finishing times around a round number and the fitted counterfactual distribution.



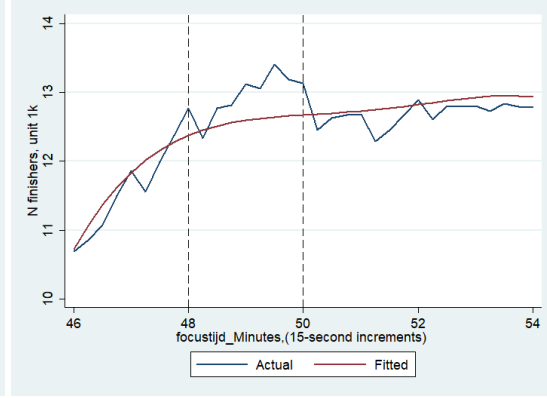
(a) rom ihoom.



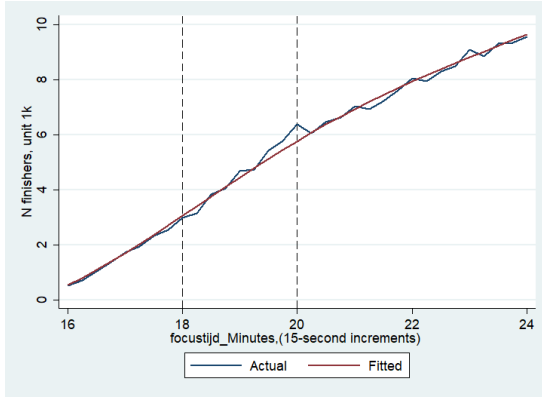
(b) 15k ihoom.



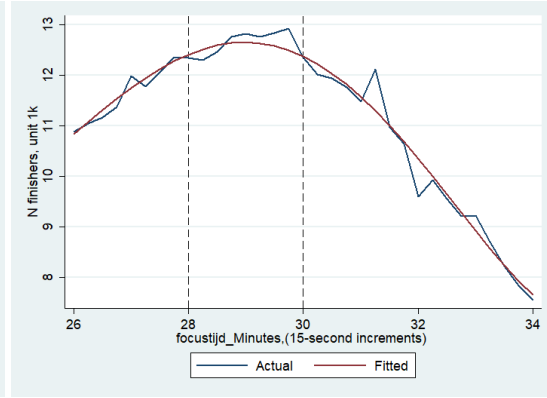
(c) 10k om40.



(d) 10k oh50m.



(e) 5k oh20m.



(f) 5k oh30m.

Figure 3: Distribution of the number of finishing times around a round number and the fitted counterfactual distribution.

Table 5: Chetty *et al.* (2011) test for selected round times.

Distance	Round time	Actual finishers	Counterfactual finishers	% excess finishers	<i>t</i> -statistic
5k	0:20	41121	39936	2.97	4.41
	0:30	113563	112872	0.61	1.58
10k	0:40	43266	41424	4.45	6.66
	0:50	116606	113074	3.12	7.76
15k	1:00	5396	4897	10.19	5.00
10m	1:00	2064	1868	10.47	3.16
21k	1:30	13823	12638	9.38	8.16
	2:00	29445	28328	3.94	5.21
marathon	3:00	2870	2159	32.92	12.03
	3:30	6701	5800	15.53	9.71
	4:00	9542	8154	17.02	12.20
	4:30	5221	4734	10.28	5.41

Note: *t*-statistics are obtained using $R = 1,000$ bootstrap samples.

distance run so far, and whether or not the runner participates as a member of an athletics club. By considering the possible relation between bunching behavior and these variables, we hope to get closer to answering the question: Do runners finish just before a round time because they evaluate runs in isolation and set a reference time for each run separately, or do they set these short term goals in light of longer-run objectives? To that end, we estimate for each distance separately the following linear probability model:

$$P(\text{Bunch}_{it} = 1) = \mathbf{X}_{it}\beta + \epsilon_{it}, \quad (3)$$

with Bunch_{it} a dummy variable with value 1 if runner i bunches in run t and 0 otherwise. As before, bunching is defined as finishing within 75-seconds before a 10-minute round time. The vector \mathbf{X}_{it} is a set of time-variant and time-invariant explanatory variables including a gender dummy, age category and the cumulative distance (and cumulative distance squared) run by runner i . The age categories used are: 5-25[years], 26-35, 36-40, 41-45, 46-50, 51-59, 60-85.¹⁷

Table 6 presents the results of these regressions. The small R^2 values are due to our definition of

¹⁷We have chosen these specific categories because they lead to about equally sized bins. To prevent outliers to drive the results, we follow the common practice to winsorize the data by taking out - per distance - the finishing times below the 1st percentile and above the 99th percentile.

bunching; a great deal of noise is involved when a runner finishes within the 75-second interval before a 10-minute time. Runners without any goal in mind will end up in this interval 12.5% ($= 75/600$) of the time and runners with a 10-minute goal in mind will often end up outside this interval because of insufficient control over their race.

A first insight from the table is that the estimate of the gender coefficient changes across runs: for the 5k distance, females seem to bunch significantly more than males. For the longer distances however, this is consistently reversed with men being up to 0.5 percentage point more likely to bunch than women. This seems at odds with the idea that runners bunch because of longer-run objectives. After all, if this is the reason to bunch, one would expect higher 5k bunching among males because they more often continue with longer distances. For more conclusive evidence on this, we need however to look into the individual careers of the bunching males and females, which we do in the next section.¹⁸

In line with the idea that runners bunch because of long-term objectives is the fact that especially for the shorter distance runs (5k and 10k) we observe that younger runners tend to bunch more than older runners. For runs longer than 10k, no correlation between age and the propensity to bunch can be detected. The table further shows that the relation between bunching and the cumulative distance run is that of an inverted U-shape, with the upward sloping part being the relevant part of the curve. In other words: the propensity to bunch increases with the cumulative number of kilometers run. Cumulative distance run can be considered a proxy for running experience. If bunching would be just a non-rational “anomaly”, field experimental evidence (List, 2003) suggests that bunching, if anything, declines with experience. Allen *et al.* (2017) do not find a clear relation between experience (in their case measured as the number of marathons) and bunching behavior.

4.3 Bunching and longer-distance run participation

We now turn to the question whether bunching or goal-setting in shorter distance runs predicts future participation in longer-distance runs. Consider an individual i who has completed a total of T runs,

¹⁸It may be tempting to relate these gender differences in bunching to the literature on gender and competition (Niederle and Vesterlund, 2007) which shows that women are more likely to shy away from competition. However, although bunching is indicative of competing against a self-set goal, there is no obvious connection with interpersonal competition. In this regard, note that the coefficient for the contest-dummy does not show a clear pattern across the columns in Table 6.

Table 6: Personal traits related to bunching

	5k	10k	15k	10m	21k	42k
female	0.0024* (0.0012)	0.0000 (0.0008)	-0.0047** (0.0018)	-0.0056** (0.0019)	-0.0032** (0.0011)	-0.0046* (0.0023)
age 26-35	0.0069*** (0.0016)	0.0022 (0.0014)	-0.0022 (0.0038)	0.0013 (0.0042)	-0.0020 (0.0024)	0.0088 (0.0051)
age 36-40	0.0087*** (0.0019)	0.0061*** (0.0015)	-0.0019 (0.0039)	-0.0019 (0.0043)	-0.0005 (0.0024)	0.0029 (0.0052)
age 41-45	0.0030 (0.0018)	0.0041** (0.0015)	0.0001 (0.0038)	-0.0008 (0.0042)	-0.0008 (0.0024)	-0.0010 (0.0050)
age 46-50	-0.0048* (0.0019)	0.0032* (0.0015)	0.0009 (0.0039)	-0.0023 (0.0042)	-0.0005 (0.0024)	0.0012 (0.0051)
age 51-59	-0.0099*** (0.0021)	0.0025 (0.0015)	-0.0025 (0.0039)	-0.0028 (0.0043)	-0.0015 (0.0024)	-0.0007 (0.0051)
age 60-85	-0.0220*** (0.0034)	0.0009 (0.0021)	-0.0087 (0.0047)	-0.0104* (0.0051)	-0.0028 (0.0029)	-0.0001 (0.0063)
CLUB	0.0146*** (0.0021)	-0.0004 (0.0013)	0.0015 (0.0021)	-0.0012 (0.0023)	0.0029* (0.0013)	-0.0033 (0.0025)
CONTEST	0.0092 (0.0047)	0.0055** (0.0020)	0.0038 (0.0031)	0.0073 (0.0040)	0.0021 (0.0029)	-0.0069 (0.0096)
cumdist	0.0001*** (0.0000)	0.0000* (0.0000)	0.0000 (0.0000)	0.0000* (0.0000)	0.0000** (0.0000)	0.0000* (0.0000)
cumdist ²	-0.0000*** (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)	-0.0000** (0.0000)	-0.0000* (0.0000)
Constant	0.1322*** (0.0012)	0.1288*** (0.0012)	0.1323*** (0.0034)	0.1321*** (0.0038)	0.1332*** (0.0022)	0.1335*** (0.0047)
Observations	710960	1180385	213604	187983	554852	154108
R ²	0.002	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses

*** (**, *) : statistically different from zero at the 0.1%-level (1%-level, 5%-level).

Dummy variables for missing age and gender included. Age bracket [5, 25] benchmark category. Errors clustered at the runner level.

with the sequence of distances run given by $d_{i1}, d_{i2}, \dots, d_{iT}$. Let d_{it}^{max} denote the maximum distance that individual i has run up to and including run t . Our interest is in the probability that an individual will participate in a longer distance run than he or she has done so far. That is, for any given t for which $d_{it}^{max} = y$, what is the probability that there exists a $t' \in (t, T]$ such that $d_{it'}^{max} = y' > y$?

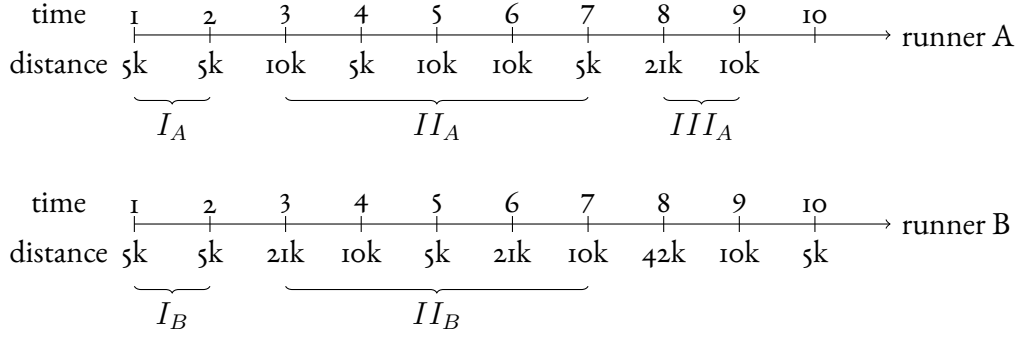


Figure 4: Careers of two runners A and B.

To illustrate the procedure we follow to establish whether bunching is related to future participation in longer races, Figure 4 presents the running careers of two runners, A and B . Runner A has participated in a total of nine runs, runner B in ten. The maximum distance run by runner A is 21k, the maximum distance run by runner B is 42k. If – conditional on having completed a 21k run – bunching and future participation in a 42k run are positively correlated, we should find a higher frequency of bunching by runner B in runs II_B than by runner A in runs III_A . To test this, we will estimate the following logistic regression:

$$P(d_{it'}^{max} = 42, \text{ for some } t' > t | d_{it}^{max} = 21) = \gamma \text{Bunch}_{it} + \mathbf{Z}_{it}\delta + u_{it},$$

$$i = 1, \dots, N; t \in \{t : d_{it}^{max} = 21\}, \quad (4)$$

with the dependent variable the probability that runner i conditional on having a 21k run as the longest completed distance, will participate in a marathon at least once. With some abuse of notation, we will write the probability on the left hand side as $P(21 \rightarrow 42)$. The vector \mathbf{Z} contains other variables that may influence whether a runner shifts to longer distances. This includes all variables included in \mathbf{X} in Section 4.2 but also running speed because low-speed runners are less likely to transfer to higher

distances.

In our estimations, we will not limit attention to the 21k to 42k transition probability, but also $P(5 \rightarrow 10)$ and $P(10 \rightarrow 21)$ probabilities.¹⁹ Returning to our example, we would use observations I_A and I_B in estimating (4) for $P(5 \rightarrow 10)$, and observations II_A to estimate (4) for $P(10 \rightarrow 21)$.²⁰ As a test of the theoretical prediction that reference dependence attenuates impulsiveness, we estimate (4) separately for men and women and interact the bunching-dummy with the age categories. The finding that impulsiveness is decreasing with age (Eysenck *et al.*, 1985), suggests that bunching behavior as a goal-setting device may especially help younger people to obtain their long run objective. In that case, we should find that γ is higher for young runners. The disturbances u_{it} will be clustered at the runner-level.

Before presenting the results we would like to make a number of comments. First, the way we define estimation samples I_A , II_A etc. is of course highly endogenous: the time at which the longer distance is run for the first time determines the final observation in the estimation sample. One should for this reason not take our estimates as an unbiased estimate of the true probability. However, for our more benign purposes this is not problematic since our interest is in the possible correlation between bunching in shorter distances and participation in longer distances. Second, whereas the above regression equation enables us to study the correlation between bunching and future participation in longer-distance runs, our data has an important limitation that disallows us to establish causality. This limitation is that we only observe a runner's finishing time and participation decision, not the actual short and long-term targets that a runner actually sets. In other words, for runners that finish outside a bunching interval, we do not know whether they missed their target or whether they did not have a target. The theory presented predicts that people finish at round times because they have longer-run objectives. The reverse however also is a possibility: that runners who manage to meet self-imposed targets are more likely to move to longer distances. Yet another possibility is that the correlation between bunching and participation in longer distance runs is driven by an unobserved third variable, e.g. self-control, that influences both people's capability to set and reach targets as well as their taste to

¹⁹In this section, we ignore the less common 15k and 10mile runs.

²⁰Note that based on the information of these two runners alone, neither the impact of bunching on $P(5 \rightarrow 10)$ or $P(10 \rightarrow 21)$ can be identified because both runners transfer to 10 and 21k runs.

run marathons.

Table 7 presents the regression estimates of equation (4). Lets focus on column (2) which shows how various variables are correlated with the probability to engage in a 21k run in the future for men, conditional on the current maximum distance being 10k. Not surprisingly, we observe that runners who are a member of an athletics club transfer to a higher distance with a much higher likelihood. This generally holds for all distance transitions and for males and female alike. In part this reflects a selection effect – runners who subscribe to an athletics club will on average have higher ambitions in running – but to some extent this may also originate from the discipline that a club and team mates provide. Another general finding is that there is a positive correlation between transferring to a higher distance and running experience (measured by the cumulative kilometers run), speed, and the current runs being 10k runs (the benchmark category being 5k runs). With regard to age, we see that for both sexes the probability of participating in higher distance runs is increasing until an age of about 36 to 45 years but is decreasing afterwards. Men aged over 60 who have never run more than 10 or 21k, are less likely to do so in the future than runners aged between 5 to 25. The same holds for women when aged over 50.

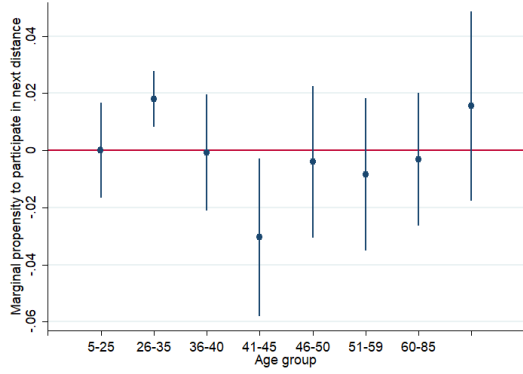
The table also shows that for none of the distances bunching is a good predictor of future participation in longer distance runs. In other words, runners do bunch but apparently not because of long-run objectives they have in mind. However, this aggregate bunching coefficient does not allow for treatment heterogeneity. If it is true that, as theory suggests, bunching is in particular an effective goal-setting device for the young and impulsive, we would expect the correlation between bunching and participation in longer distance runs to be higher for younger runners. Therefore, we have also interacted the bunching dummy with the age categories, Figure 5 depicts the marginal effects. For none of the sexes or distance transitions, there is an indication that younger runners who bunch are more likely to continue running longer distances than their non-bunching peers. This leads us to conclude that there is no evidence that individuals finish just before a 10-minute time because they are motivated by the objective to participate in longer runs in the future.

Table 7: Logit estimates future longer distance participation

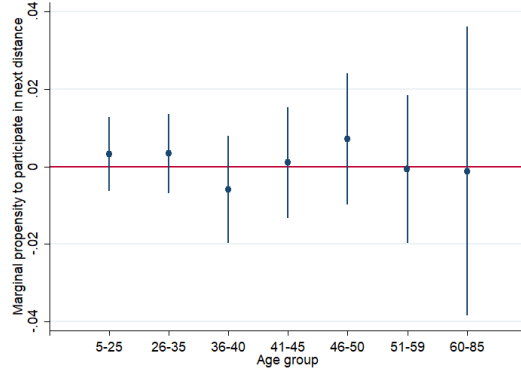
Dep. var	Males			Females		
	(1) $P(5 \rightarrow 10)$	(2) $P(10 \rightarrow 21)$	(3) $P(21 \rightarrow 42)$	(4) $P(5 \rightarrow 10)$	(5) $P(10 \rightarrow 21)$	(6) $P(21 \rightarrow 42)$
Bunch	0.034 (0.021)	0.020 (0.013)	0.004 (0.012)	0.020 (0.016)	-0.004 (0.017)	0.033 (0.021)
age 26-35	0.871*** (0.028)	0.562*** (0.029)	0.355*** (0.051)	0.664*** (0.023)	0.105** (0.033)	0.013 (0.083)
age 36-40	1.201*** (0.034)	0.806*** (0.031)	0.561*** (0.054)	0.813*** (0.026)	0.333*** (0.036)	0.254** (0.085)
age 41-45	1.147*** (0.033)	0.827*** (0.031)	0.516*** (0.054)	0.791*** (0.027)	0.363*** (0.036)	0.193* (0.085)
age 46-50	1.093*** (0.037)	0.673*** (0.033)	0.348*** (0.055)	0.665*** (0.032)	0.238*** (0.040)	0.029 (0.088)
age 51-59	0.869*** (0.040)	0.396*** (0.035)	0.008 (0.059)	0.513*** (0.039)	-0.132** (0.050)	-0.459*** (0.100)
age 60-85	0.416*** (0.069)	-0.132* (0.058)	-0.703*** (0.092)	-0.224* (0.112)	-0.802*** (0.115)	-1.312*** (0.191)
CLUB	0.318*** (0.040)	0.558*** (0.029)	0.460*** (0.036)	0.306*** (0.034)	0.600*** (0.035)	0.465*** (0.054)
CONTEST	-0.625*** (0.070)	-0.168*** (0.032)	0.231*** (0.032)	-0.485*** (0.066)	-0.063 (0.046)	0.277*** (0.060)
cumdist	0.017*** (0.002)	0.003*** (0.001)	-0.000 (0.000)	0.013*** (0.002)	0.010*** (0.001)	0.004* (0.002)
cumdist ²	-0.000*** (0.000)	-0.000* (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000*** (0.000)	-0.000 (0.000)
Speed	0.296*** (0.046)	1.053*** (0.050)	0.971*** (0.075)	1.159*** (0.062)	1.887*** (0.086)	1.422*** (0.150)
Speed ²	-0.004 (0.002)	-0.033*** (0.002)	-0.031*** (0.003)	-0.041*** (0.003)	-0.070*** (0.004)	-0.052*** (0.007)
Distance:						
10		0.498*** (0.028)	0.516*** (0.040)		0.512*** (0.027)	0.470*** (0.056)
15			1.054*** (0.044)			1.096*** (0.063)
16			0.923*** (0.044)			0.808*** (0.066)
21			0.971*** (0.042)			0.856*** (0.063)
Constant	-4.977*** (0.278)	-10.154*** (0.310)	-9.835*** (0.458)	-9.430*** (0.319)	-14.602*** (0.474)	-12.135*** (0.854)
obs.	191,082	418,830	659,406	256,684	310,350	217,357
pseudo R^2	0.062	0.047	0.053	0.048	0.054	0.052

Standard errors in parentheses; ***(**, *): statistically different from zero at the 0.1%-level (1%-level, 5%-level).

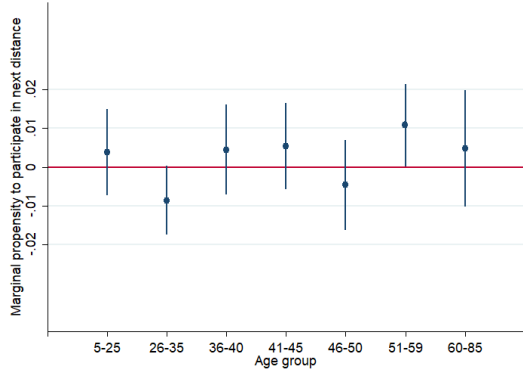
Benchmark categories: age 5-25; VILLAGE; RECREATIVE; Distance=5k. Errors clustered at the runner level.



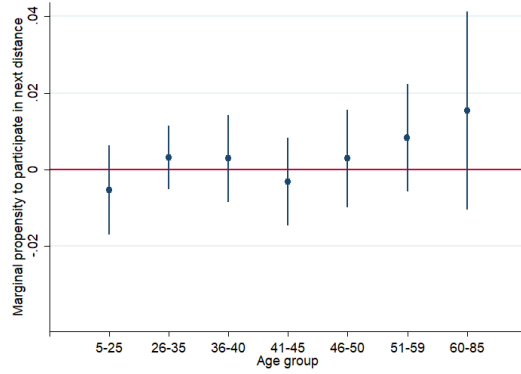
(a) Males: $P(5 \rightarrow 10)$.



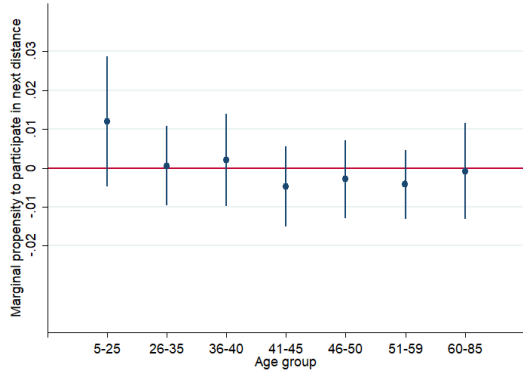
(b) Females: $P(5 \rightarrow 10)$.



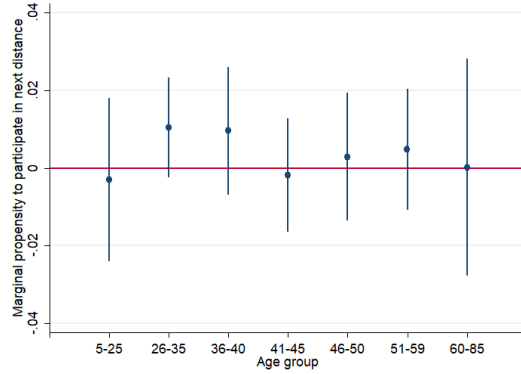
(c) Males: $P(10 \rightarrow 21)$.



(d) Females: $P(10 \rightarrow 21)$.



(e) Males: $P(21 \rightarrow 42)$.



(f) Females: $P(21 \rightarrow 42)$.

Figure 5: Marginal effect of bunching on participation in longer distances

5 Summary

In this paper, we consider the prevalence of reference points in sport activities using a new data set covering organized runs of different distances in the Netherlands in the period 1996-2016. In line with other recent studies we find excess mass just before the 10-minute round times for the marathon, but also for the shorter 5k, 10k and 21k runs. This indicates that a non-negligible sub-sample of runners sets themselves a round time-goal in individual runs. The question what motivates runners to set such time goals has however not yet been answered. Guided by recent theory on goal-setting, we explore one potential motivation for bunching behavior: short-term goals help people to overcome self-control problems and thereby to reach more distant objectives. Translated to our running context, this may imply that runners who bunch are more likely to participate in longer distance runs in the future. We empirically test this hypothesis but do not find any evidence. Runners who finish at a round time goals are not any more likely to switch to longer distances than others. This negative result continues to hold if we zoom in on the younger runners, who allegedly are more impulsive and thus would benefit more from goal-setting. In sum, our empirical evidence does not support the hypothesis that the bunching observed in our data is motivated by the presence of longer-run objectives. More research on this topic using innovative designs is welcomed.

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Online Appendix

A Data Set Construction

The data were retrieved from the web site www.uitslagen.nl, an public online data base were organizers of running events in the Netherlands can post results. All posted results, 6,544,393 in total, were downloaded at September 1, 2016. The data contain the following variables:

name: Name of runner, given name and family name;

wnplsver: Village or affiliation (team or school) runner;

birthyr: Year of birth;

bruto: Gross time;

netto: Net time;

event: Name of running event;

locationdate: Location and date of the running event;

type: Running subcategory in which runner participated (gender, distance);

place: Place in ranking of runner within the subcategory.

All observations without information on ‘name’, ‘wnplsver’ and ‘birthyr’ have been discarded (1,206,499 observations in total). Also the observations that mentioned ‘starting number’ or ‘municipality’ as name (8,332 and 333 observations) have been discarded. Then there were names consisting of numbers (e.g. “03 01 2006 19:41”). We kept these observations (3,196 in total) in our initial sample but constructed a variable “individu” which received the value “NOIDVLNAME” (meaning: individual cannot be identified by listed name) for these observations.²¹ The variable `individu` receives the value `FIRM` if the name contains a company name such as ‘shell’, ‘aramco’, ‘rabobank’ etc.

²¹Other observations that received the value `NOIDVLNAME` for the variable `individu` are records without name (18 cases), and records of which name starts or ends with a number, the name starts with a special character or has the phrase “av”, “team” or “athletics” in it. These are about 6,000 cases in total.

A.1 Runner identification

Based on the above variables, a number of identifying keys have been constructed:

`idxEVENT` An event identifier;

`idxEVENTsubcat` An identifier for the subcategory of the event;

`idxRUNNERinitial` A runner-specific ID based on the name and birth year information *before* the data manipulations described below;

`idxRUNNER` A runner-specific ID based on the information *after* the data manipulations described below.

To start, all unique name and birthyear combinations are given their own identifying ID, `idxRUNNERinitial`. This implies that individuals with the same name but a different or missing birth year get assigned a different ID. For this reason, the number of distinct initial IDs (1,855,081) is an upper bound for the number of unique runners in the data set.

However, absent a central registry, runners need to fill in their personal details every time they sign up for a run. This implies that the same individual often is registered under different names, dependent on whether the full name or only one or more initials are used (“jan jansen”; “j jansen”, “j m jansen”) or simple spelling mistakes (“jan janssen”, “jan janse”). The same holds for the place of residence. The same runner may appear with different places of residence just because he or she has moved but a runner may also participate in some runs by mentioning his/her home address (“Amsterdam”) and in others the athletics club (“Hellas”) or school (“University of Groningen”) to which (s)he is affiliated. Typo’s may also lead to different entries for the same individual (“1947” and “1974”).

These issues were dealt with in the following way. The observations were sorted on year of birth, village or affiliation (in that particular order) and then the similarity of the given and family name of each two subsequent observations was measured using the Jaro-Winkler distance (Winkler, 1999). The Jaro-Winkler distance has been developed specifically to detect duplicates in record linkage that result from typo’s. The Jaro-Winkler distance metric returns a value between 0 and 1. A score of 0 means an exact match and a score of 1 implies no similarity. One feature of the Jaro-Winkler distance

metric is that the substitution of two characters that are close are considered less important than the substitution of two characters further apart.

We use a threshold value of 0.15 with all pairs of names being considered duplicates if the Jaro-Winkler score on both the given and family name was smaller or equal to 0.15. This rule however does not detect as duplicates two names that differ in the given name because in one case more initials are recorded than in the other. To account for this, two pairs of names are also considered duplicates if the first given name or initial is exactly identical and the Jaro-Winkler score for the family name is 0.10 or less.

For a considerable number of running events, the year of birth is not recorded. We decided to identify two individuals as the same person when they are the two unique individuals who share name and place of residence, but for one of them the year of birth is missing.

Two individuals who share a unique name but not `wnplsver` are considered the same person only if there are no other individuals with the same name and if they have the same year of birth or the year of birth of one of the two is missing. This to some extent accounts for the fact that a large group of runners participates under different affiliations, e.g. their place of residence and their athletics club.

Given the many different names and birth years under which individuals appear, this procedure overstates the number of different runners.²² We chose a conservative approach because the opposite – grouping results of different individuals as if they are the same person – is worse.

A.2 Identification of gender

To identify a runner's gender, we matched the first given name of each observation with a data base of the 10,000 most common given names in the Netherlands.²³ In case of a match, the result can be that the runner is classified as a male, female or ambiguous (some names like "Anne" are used for boys and girls). In case of no match, the second and third given name are considered to identify the gender. In total, in 4,797,905 cases the gender of the runner can be determined (2,920,426 male observations;

²²e.g. (egbert hogerweij sisu 1944; egbert hogerweij sisu 1944) is considered a different individual than (egbert hogerweij almelo 1945; egbert hogerweij almelo 1945; egbert hogerweij almelo) and (egbert hogerweij amersfoortse verzeke). Probably it is the same person but they are counted as three different individuals.

²³This data set was downloaded from http://www.naamkunde.net/?page_id=293 on July 14, 2017. This data base contains all given names that have been given 27 times or more to children born in the Netherlands in the time period 1983-2006 according to the administrative records of the Sociale Verzekeringsbank.

1,499,673 female and 377,806 ambiguous). Note that this identification method only uses name information from single runs. Considering all runs by a single individual further improves the gender identification (for example, “c kruit” will be classified as ambiguous but when it turns out that this person participated under the name “chantal kruit” in other runs, she can be classified as female). Another source of information is the name of the subcategory in which the individual participated. For example, when this name is “10k run ladies 30-45y” we know that the individual is a female. To establish the ‘final’ gender of a runner, we combine name information (across runs) and subcategory information. This procedure leaves 59,912 runners unclassified in terms of gender.

A.3 Identification of birth year

Years of birth before 1900 were set to missing, just as years beyond 2016. When only the final two or three digits of a year were mentioned, this number was completed to four digits. Cases where the year of birth entry contained non-numerical characters were set to missing.

A.4 Identification of affiliation

Based on the variable `wnplsver` a variable ‘`affiliatie`’ is constructed which says whether has filled out his village, province, club or school affiliation on the form. The variable assigns the value “CLUB” if there is a match with one of the names of athletic clubs in the Netherlands²⁴ or when `wnplsver` contains the one of the words “av”, “loopgroep”, “loopteam”, “atletiek”, “athletics” or “runners”. `affiliatie`=VILLAGE if there is a match with one of the official village names in the Netherlands.²⁵ Other values for `affiliatie` are PRIMSCHOOL (for primary schools, abbreviations “cbs”, “obs” “rkbs” etc.), SEC school (secondary school), UNIVERSITY, PROVINCE (for each of the twelve Dutch provinces), NEDERLAND and NONE (if `wnplsver` is blank). In this way, a total of 1,395,597 can be assigned a value for `affiliatie`: VILLAGE (1,040,792), CLUB (183,597), NONE (133,568), SECSCHOOL (14,961), NEDERLAND (11,135), PRIMSCHOOL (10,715) and PROVINCE (116).

²⁴The list of names of these clubs was taken from the web site https://nl.wikipedia.org/wiki/Lijst_van_Nederlandse_atletiekverenigingen, visited July 24, 2017.

²⁵This list was obtained from <https://home.kpn.nl/pagklein/almanak.html>, visited July 20, 2017.

A.5 Identification of distances

The variable `type` contains the information on the distance that is run. For example, “M40, 10 KILOMETER” says that the runner participated in a run over 10 kilometer for men aged 40 and above. Some care had to be taken because, dependent on the context, “10m” may mean 10 miles, 10 meter or men aged 10 and above. There are multiple ways to denote a distance, with a half marathon for example being written as “halve marathon”, “21.1km”, “hm” and “hmtn”. For a total of 110,526 subcategories of events (out of 141,168), the distance has been determined based on the information in `type`. Of the events without a distance, 264 events concerned a Cooper test where participants run a fixed time instead of a fixed distance, 476 a relay race.

A.6 Recreational and competitive runs

Runs can be competitive or recreative and it is common to organize a competition within a run for a selected number of athletes. For example, the first runners that start in a marathon often are (semi-)professionals who receive money to participate. They compete to win a prize and/or to set a new track record. They are then followed by the recreational athletes. Based on the information retrieved from the `type` variable, a variable `Contest` has been constructed that takes on the following values: `CONTEST` if the runner is in a competition; `KIDS/YOUTH/STUDENT` if the run is classified a so-called ‘kids run’, ‘youth run’ or ‘student run’; `SCHOOL` if the run is organized by school(s), and `RECREATIVE` if no formal contest element is present. A total of 22,330 runs receive one of these qualifications.

A.7 Estimation sample

The file `RunRecordsFINAL.dta` contains 5,321,614 unique running results participating in a total of 10,703 events (based on `idxEVENT`). In 19,261 cases, no finishing time is provided. Another 983,678 records have no distance attached to them, these are observations from street runs of unspecified length. Of the finishing times with a distance attached, 1,218,817 concern finishing times for runs other than the 5k, 10k, 15k, 10m, half marathon or marathon distance that are the object of our analysis. We also discard 11,635 observations ($< 1\%$) because the implicit average speed exceeds that of the world

record at that particular distance. Finally, we discard all finishing times by individuals with a recorded age lower than five or higher than 95 (1,254 observations in total $< 0.1\%$). This leaves us with an estimation sample of 3,086,969 finishing times for 1,020,629 unique runners participating in a total of 7,159 different events, see Table A1. For the part of the analysis that uses the panel property of our data, we leave out 2,034 “non-individual” results. These finishing times have been set by people who participated for example as employee of a firm and appear in the data as, for example “ING team 1”.

Table A1: From initial to estimation sample.

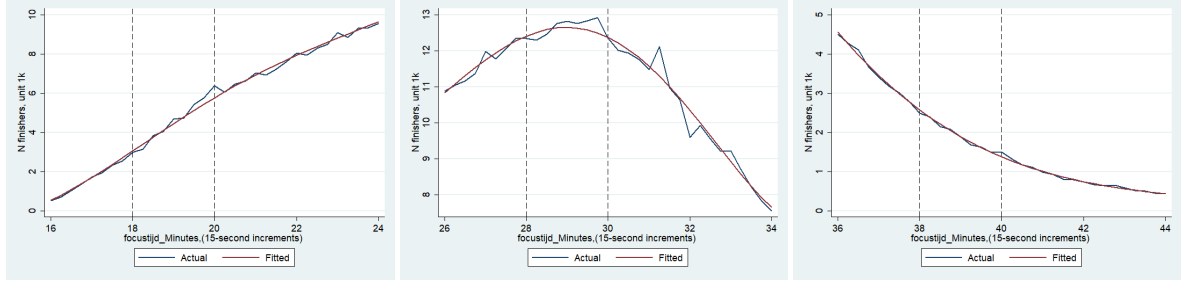
		Finishing times	Runners	Events
# Unique records		5,321,614	1,599,845	10,703
no time provided	19,261			
no distance provided	983,678			
non-major distance	1,212,988			
faster than WR	2892			
(nordic) walking	12834			
cycling or skeelering	14155			
Dropped total		2,245,808		
		3,075,806		
non-individuals		1917		
age ≤ 5		1236		
age ≥ 85		344		
Estimation sample		3,072,309	1,013,398	7,123

—

Individuals aged lower than 5 (4,122 observations) and higher than 95 (193 observations) have also been discarded.

This leaves us with 5,296,217 results of 755,574 runners (based on `idxRUNNER`), . For the major distances, 5k, 10k, 15k, 10 mile, half marathon and full marathon, these numbers are 3,258,580; 1,106,609 and 7,527, respectively.

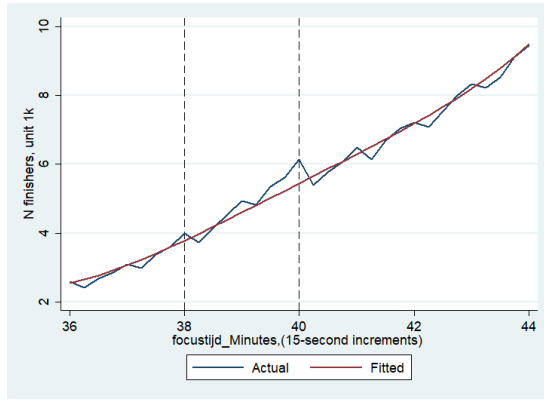
B Additional Graphs and Tables



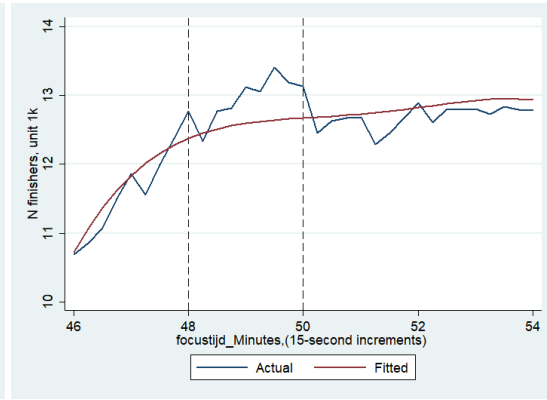
(a) 5k – oh2om.

(b) 5k – oh3om.

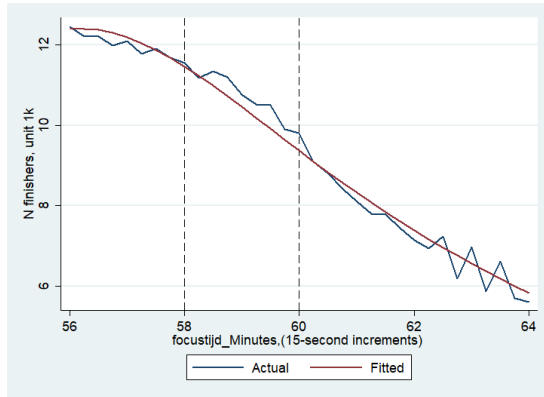
(c) 5k – oh4om.



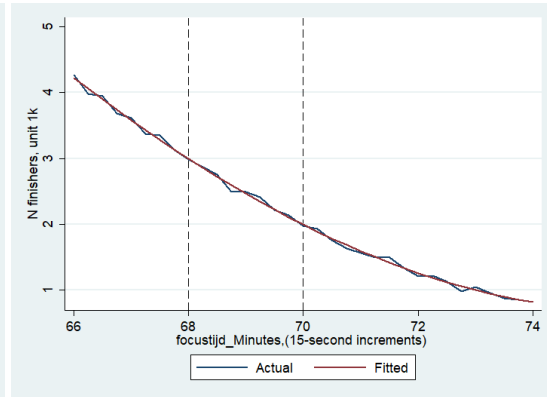
(d) 10k – oh4om.



(e) 10k – oh5om.



(f) 10k – 1moo.



(g) 10k – 1h1om.

Figure A1: Distance: 5k and 10k. Distribution of the number of finishing times around a round number and the fitted counterfactual distribution.

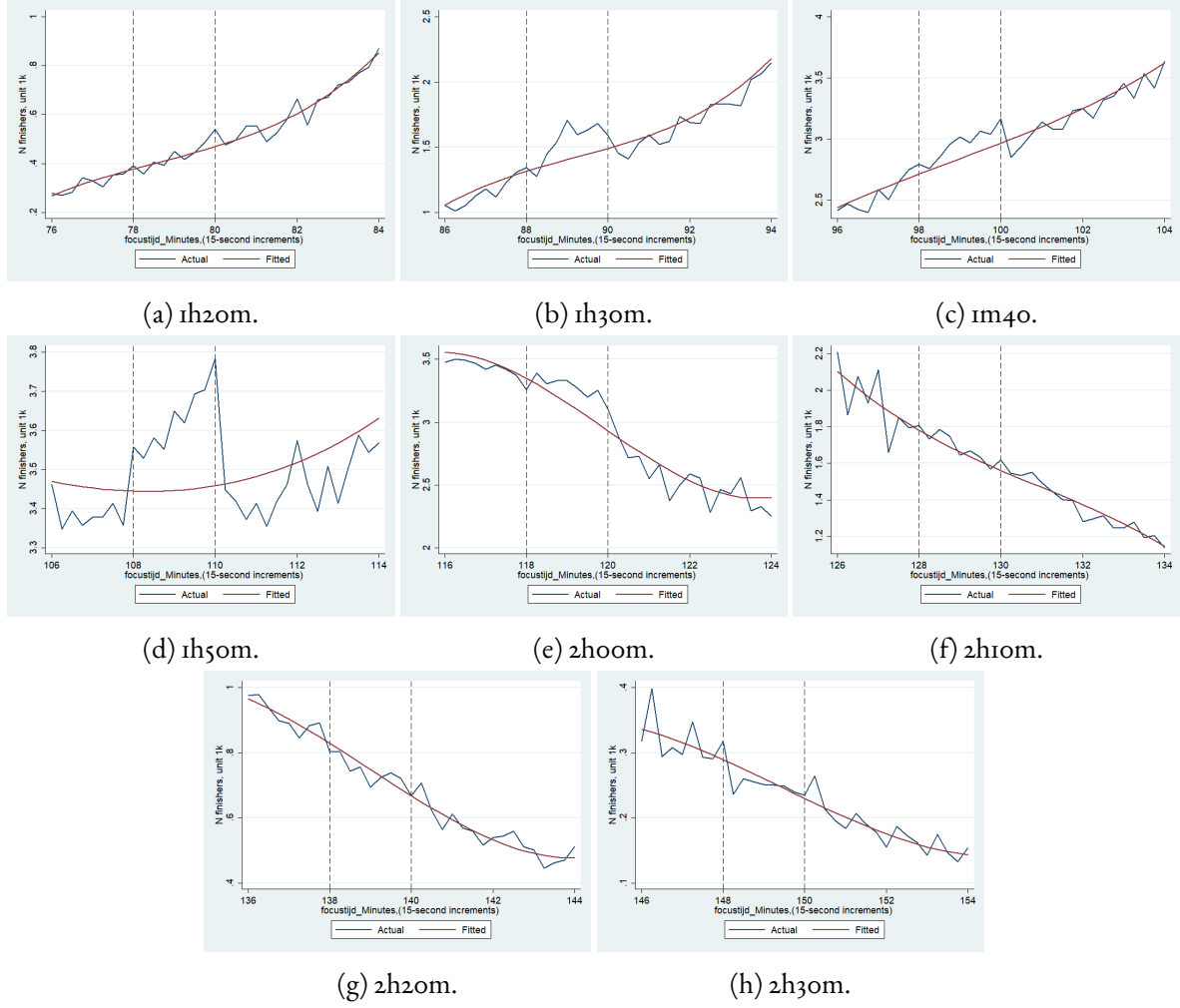


Figure A2: Distance: half marathon. Distribution of the number of finishing times around a round number and the fitted counterfactual distribution.

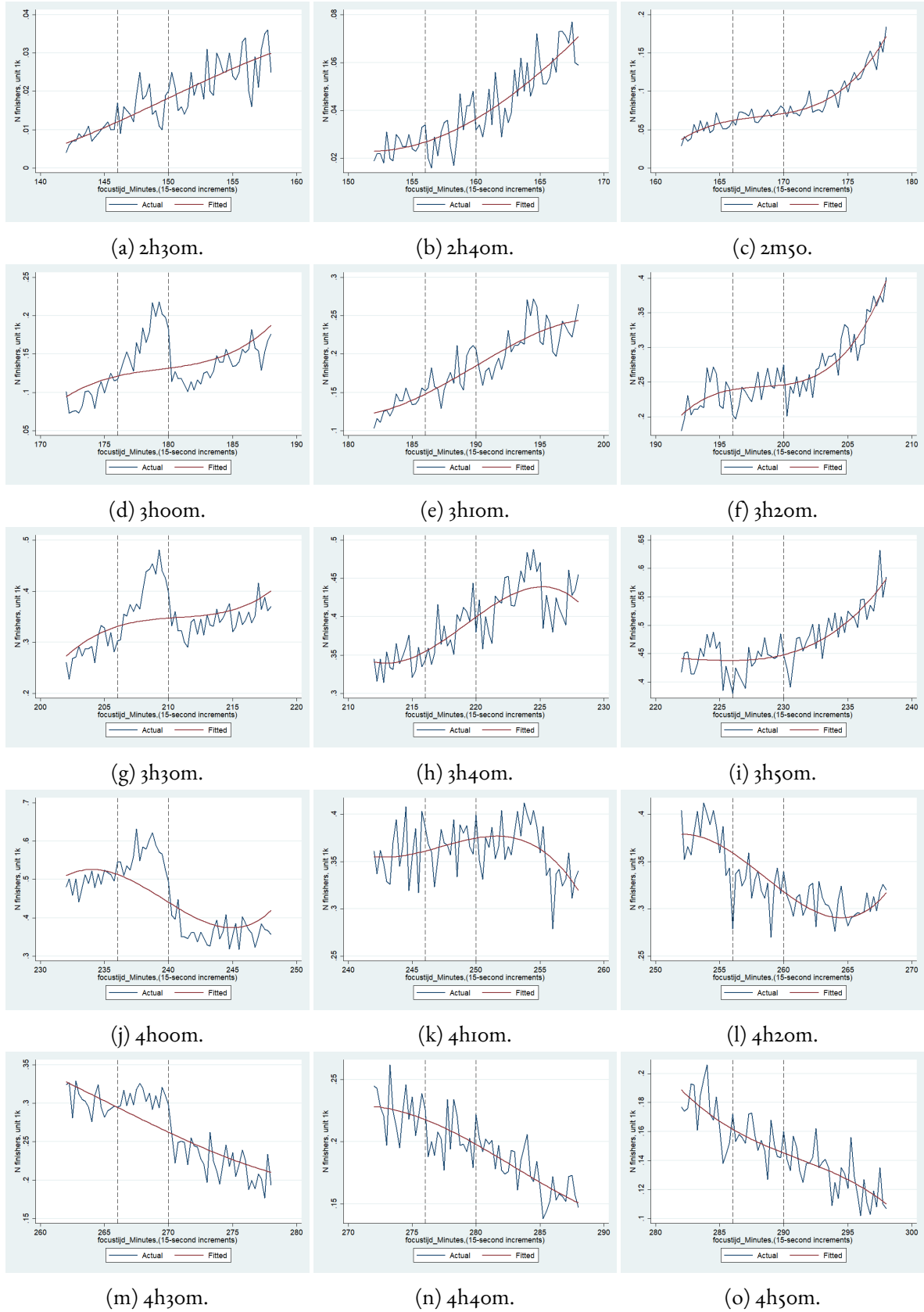


Figure A3: Distance: marathon. Distribution of the number of finishing times around a round number and the fitted counterfactual distribution.

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